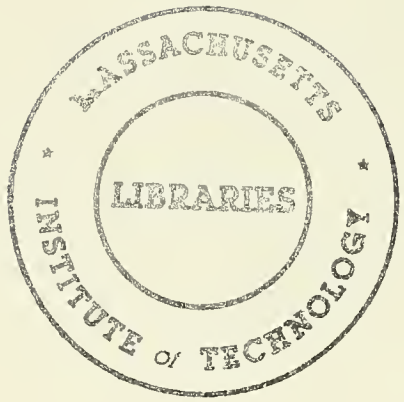
MIT LIBRARIES
3 9080 00367 2109


MASSACHUSETTS
LIBRARIES
INSTITUTE of TECHNOLOGY

Digitized by the Internet Archive
in 2011 with funding from
Boston Library Consortium Member Libraries

http://www.archive.org/details/probabilityofdep00barr

HB31
.M415
no.131

JAN 24 '74

working paper
department
of economics

THE PROBABILITY OF DEPENDENCE ON PUBLIC ASSISTANCE

Nicholas A. Barr
London School of Economics

Robert E. Hall
M.I.T.

Number 131 May 1974

massachusetts
institute of
technology

50 memorial drive
cambridge, mass. 02139

MASS. INST. TECH.
JUN 24 '74
DEWEY LIBRARY

THE PROBABILITY OF DEPENDENCE ON PUBLIC ASSISTANCE

Nicholas A. Barr
London School of Economics

Robert E. Hall
M.I.T.

Number 131 May 1974

This research was supported by the Ford Foundation. We are grateful to David McClain for assistance, and to Rachel McCulloch and Frank Levy for comments.

HB 31
.M415
no. 131

RECEIVED
JUL 1 1974
M. I. T. LIBRARIES

Programs for redistributing income to the poor face an inevitable conflict between the need to preserve incentives to work by imposing a less than confiscatory tax rate on earnings, on the one hand, and the desire to concentrate the benefits of the programs among the poorest families, on the other hand. Many issues in the design of redistributional policies are empirical, and can only be answered through the detailed examination of the behavior of actual and potential beneficiaries of the programs. In this paper we present the results of an extensive study of the response of an important group of poor families, those without fathers, to the largest single redistributive program now in operation, Aid to Families with Dependent Children. We attempt to answer the following questions:

1. How effective is AFDC in selecting the very poorest for the largest benefits?

2. To what extent do recipients take advantage of the opportunity to supplement benefits with earnings? How do they respond to alternative levels of the implicit tax on earnings?

3. How does the caseload depend on the generosity of benefits and on the implicit tax on earnings?

4. Does the disproportionate share of blacks among recipients reflect a difference in attitudes about work and welfare between blacks and whites, or can it be explained by the adverse circumstances of blacks?

The study focuses on the probabilities of four alternative levels of dependence: none, partial (benefits less than earnings), substantial (benefits more than earnings), and total. These probabilities are taken as functions of family characteristics and of the parameters of the AFDC system. For example, the probability that a mother will be fully dependent

0721180

declines as her wage rises. Section 1 of the paper develops the theory of family behavior, starting from the assumption that the observed dispersion in the behavior of apparently identical families reflects an underlying distribution of unobserved differences among them. Section 2 discusses the statistical method used to estimate the probabilities, a straightforward generalization of the binary logit and probit methods. Section 3 describes the data, which were taken from a survey of welfare recipients and from the Survey of Economic Opportunity. Section 4 presents and interprets the statistical results.

The effectiveness of AFDC in concentrating its benefits among poorer families is measured in two ways in our study: through the influence of the potential wage of the mother and through the influence of the unearned income of the family. Both have a strong effect in the expected direction, suggesting that the program is reasonably successful in bringing about a redistribution of income. For example, 91 percent of families with certain characteristics and potential wages of $1.50 per hour are at least partly dependent, but only 56 percent of otherwise identical families with potential wages of $3.00 per hour. Similarly, only 42 percent of families are at least partly dependent if their unearned incomes are $200 per month, against 91 percent of those with no unearned income.

Our results suggest that an important minority of dependent families supplement welfare benefits with earnings. In general, around 7 percent have earnings that exceed their benefits, and another 4 percent have lower but positive earnings. These probabilities are sensitive both to family characteristics and to the formula under which benefits are paid. Mothers with children of preschool age or whose health is poor are less than half as likely to work. The implicit tax rate on earnings (the amount by which

benefits are reduced for each additional dollar of earnings) is a particularly important determinant of the probability of work among dependent mothers. In cities that tax earnings at the rate of 20 percent about 13 percent work, while in cities with rates of 60 percent and the same base level of benefits only 8 percent of dependent mothers work. Our sample includes cities at both of these extremes.

The formula under which benefits are paid is an important determinant of the probability of dependence. In an earlier paper, we developed an empirical characterization of the effective tax rates on earnings and other forms of income imposed by AFDC, and of the lump-sum component of assistance, considered as a function of various family characteristics. All families receive the lump-sum payment, and those with earnings are permitted to retain earnings remaining after deduction of the tax. In this paper, we deal mainly with the two most important parameters of the system of benefits: the lump-sum transfer, λ, and the implicit tax rate on earnings, θ. In our results, higher values of λ are associated with higher probabilities of dependence. If λ is \$200 per month, 81 percent of families are fully dependent, but if λ is \$250, 91 percent are dependent. We have also calculated the costs of alternative values of λ. The \$50 increase just mentioned costs \$48 per family and is associated with an average reduction in hours of work of about 10 percent. Similar calculations for the tax rate, θ, yield one important surprise: Increasing θ reduces the probability of dependence, as expected, reduces the average hours of work among recipients, again as expected, but actually <u>increases</u> the average hours of work in the whole population. The view prevalent among economists that raising the tax rate on earnings reduces labor supply may be incorrect. It misses the point that the fraction of the population on welfare shrinks as θ increases, and individuals work more when they are off welfare than when they are on it.

Finally, no important differences between blacks and whites are revealed in the study. In fact, after taking account of education, health, number and ages of children, and potential wage, we find that whites are slightly more likely than blacks to be on welfare. Since we take the population of families without fathers as given, our study sheds no light on differences between the stability of black and white families. Our results suggest that the higher fraction of dependent black families compared to white families derives from the higher fraction of fatherless black families and the adverse education, wages, and other characteristics of blacks, and not from any differences in attitudes about welfare.

1. Theory

In any study of the behavior of individuals, it is essential to take account of the diverse behavior of similarly situated individuals. Among low-income families, only a fraction receive public assistance; most of the others have decided against applying for assistance in spite of their eligibility for it. Our formal theory takes account of variations in behavior through the assumption that there are unobserved differences in tastes, attitudes, and other characteristics among families. These include the taste or need for purchased goods and for time spent at home, the stigma attached to the receipt of public assistance, and unmeasured determinants of productivity at home or at work. Our theory starts with a description of the behavior of a family with given values of these unobservable variables. At this stage the behavior is assumed to be deterministic. We then consider the probability distribution of individual responses that we observe by drawing repeatedly at random from a population with diverse unobserved characteristics. Our assumptions about the response of individual families to changes in the parameters of the budget constraint--the wage, unearned income, lump-sum transfer of AFDC, and the implicit tax on earnings--translate into predictions about the response of the observed probabilities to changes in these parameters.

Behavior of individual families

We assume that the family head makes decisions in the following way: First she considers the highest level of family satisfaction obtainable without assistance, subject to the budget constraint that purchases of goods must be financed through unearned income, y, and earnings, wH (w is the hourly

wage and H is the number of hours of work). She then compares this level of satisfaction to the level obtainable under public assistance, subject to the modified budget constraint that purchases of goods must be financed through the amount of unearned income remaining after the tax imposed by the system of assistance, $(1 - \tau)\, y$, the amount of earnings remaining after tax, $(1 - \theta)\, wH$, and the lump-sum component of assistance, λ. Finally, she decides to seek assistance if the second level of satisfaction exceeds the first.[1] Satisfaction is defined comprehensively to include foregone time at home and the stigma of receiving assistance. For the moment we neglect the distinction between seeking assistance and actually receiving it.

We represent the outcome of this process as follows: First, we define a normalized measure of dependence, z, as the ratio of benefits, b, to the sum of benefits and earnings, wH:

$$z = \frac{b}{b + wH} \tag{1.1}$$

It varies between 0, for a family not on welfare, to 1 for a family that is fully dependent and has no earnings. Then we describe the joint family decision about work and dependence on welfare through the function f, which takes account of all of the economic considerations as well as the vector of unobserved characteristics of the family, t:

$$z = f(w, y, \theta, \lambda, \tau, t) \tag{1.2}$$

---

[1] Brehm and Saving developed a theory along these lines, and were later criticised by Albin and Stein. See Barr, Chapter 4, for a complete discussion.

We expect the following about the response of z to the arguments of f:

1. It decreases with the wage, w. The more attractive work is in the market, the less dependent the family is. Even if hours of work remained unchanged as w rose, earnings would rise and benefits fall, so z would fall. We also would expect hours of work to rise, making z fall even further.

2. It decreases with outside income, y, unless the tax on it, τ, is low and hours of work are very sensitive to y.

3. Its dependence on the tax rate on earnings, θ, is ambiguous. Assistance is made less attractive to a prospective worker by a higher tax rate, but those who are already on welfare may work less and become more dependent as θ rises. An important goal of this paper is to measure the relative strength of these effects.

4. It decreases with the tax rate on unearned income, τ, and increases with the lump-sum transfer, λ. An unambiguous increase in the generosity of assistance increases dependence.

The dependence function, f, is deterministic within this framework. A family with given characteristics, t, will behave in a predictable way. Over a wide range of values of the parameters w, y, θ, λ, and τ, dependence will always be zero, either because the opportunities off welfare are unattractive (high values of θ and τ or low values of λ). Similarly, there is a range of values where it is always one--families are fully dependent because not even the first hour of work pays off. Between these two ranges, there is a presumption that dependence responds discontinuously to changes in its determinants for any particular family. At zero dependence the marginal rate of substitution between time at home and goods is the wage, while at any positive level of dependence it is the wage adjusted for the substantial tax on

earnings imposed by public assistance. Consequently, the decision to opt for assistance at any level should be accompanied by a discontinuous decline in hours of work. This in turn makes z jump discontinuously from zero to a positive value well above zero. In fact, our empirical results suggest that for many families the decision about assistance is all or nothing--they choose between full time work without assistance or no work and full assistance. This discontinuity of behavior is precisely compatible with rational decision-making guided by marginal considerations.

Implications of the diversity of unobserved characteristics

The observer can only make a probabilistic statement about the likely behavior of a family because some of its important characteristics are unknown. Within a group of families with identical observed characteristics, facing the same economic alternatives, the most information we can hope to obtain is the probability distribution of our measure of dependence. This distribution is induced by the underlying diversity of tastes and attitudes about work and welfare. The probability that a family drawn at random will have a given degree of dependence is the fraction of the total population whose characteristics are such that they have that degree of dependence. For example, the probability that a particular family will be off welfare altogether when faced with specified parameters is the fraction of the population whose level of satisfaction is lower for any positive level of dependence than it is at zero dependence. We deal with probabilities not because we believe that there is an important random element in individual choices but because our sample is chosen randomly from a diverse population.

The behavior of the individual family is sensitive to economic parameters, so the probabilities just defined are also sensitive to them. The fraction of

families opting for assistance rises as the system becomes more generous, because families whose preferences and other characteristics put them near the threshold will switch from zero dependence to some positive level. Even though the behavior of each switching family is discontinuous, the probability of dependence is a continuous function of its economic determinants, as long as the distribution of unobserved characteristics is smooth.

These considerations justify the following formal approach: We consider the probability distribution of our measure of dependence, z, with a population of families facing parameters w, y, θ, λ, and τ, and are interested in showing how the distribution shifts as these parameters vary. We combine the parameters into a vector, x, to which we also add other relevant observed characteristics of the family (race, education, age, and health of the mother, number of adults and children, and length of residence). Then we define P(Z,x) as the fraction of the population of families with characteristics x who have a degree of dependence no greater than Z. P(0,x) is the fraction who are not dependent at all and P(1,x) is 1, since z cannot exceed 1. P(Z,x) is a hybrid probability distribution: it assigns substantial probability to the two extreme values of z, 0 and 1. Between these values it is presumably a smooth distribution and does not assign positive probability to any single value of z. Previous econometric studies of random variables that are bounded in this way, deriving from the famous Tobit model of James Tobin, have specified a density function for the distribution between the extremes. In our case, however, we are most interested in the two extremes, and have little prior information about the distribution between the extremes (the probability of an intermediate value of z varies between about 10 and 25 percent for different values of x). We have adopted a somewhat less restrictive specification than the Tobit model, involving the study of four discrete probabilities:

$p_0(x) = P(0,x)$, the probability of not being on welfare;

$p_1(x) = P(0.5,x) - P(0,x)$, the probability of partial dependence;

$p_2(x) = P(0.99,x) - P(0.5,x)$, the probability of substantial dependence, and

$p_3(x) = 1 - P(0.99,x)$, the probability of essentially total dependence.

Response of probabilities to economic determinants

Our earlier argument suggests that each of the probabilities just defined is a continuous function of its arguments. Our expectations about the response of individual behavior to changes in economic determinants translate into similar expectations about $p_0(x)$--it should increase with w, y, θ, and τ, and should decrease with λ. Attractive opportunities for income when off welfare and unattractive welfare parameters increase the fraction of families that opt against welfare. Note that we can be confident of the impact of θ, the tax rate on earnings, on the probability of being off welfare even though we are uncertain about the effect of θ on all families--no family previously off would go on welfare as a result of an increase in the tax rate. The response of $p_3(x)$, the probability of total dependence, is similarly clear. It should decrease with w, y, and λ, and should increase with θ and τ. Again, no fully dependent mother would decide to go to work if the tax rate on earnings rose. The responses of the probabilities of partial and substantial dependence to their economic determinants are generally ambiguous--as welfare becomes more attractive, families move into these categories from below but others move from them to higher categories. However, the response of the combined probability of intermediate degrees of dependence, $p_1(x) + p_2(x)$, to the tax rate, θ, is unambiguous,

since $p_0(x)$ and $p_3(x)$ respond in the same direction and the four probabilities sum to one: A higher tax rate on earnings discourages mothers from combining earnings and assistance, and makes the decision about welfare more one of all or nothing.

Qualifications

So far we have treated the theory of dependence on public assistance as an application of the theory of consumer choice. The head of the household studies the alternatives defined by the budget constraint and chooses a plan that maximizes family satisfaction. The only departures from the usual treatment of the theory of the consumer arise from the nonlinearity of the budget constraint and from our explicit assumption of diversity in preferences. We maintain the basic assumption that consumers make voluntary choices within a fixed budget constraint. Two main objections will be made to our theory: First, public assistance does not present a clearly defined fixed set of alternatives. Rather, potential applicants face uncertainty about whether or not they will be accepted for AFDC and if so what payments will be made at various levels of earnings. Second, they face uncertainty about the availability of employment at the desired number of hours per week.

To an extent, we are able to take account of systematic differences in the economic opportunities available to different groups in our sample. For both public assistance and employment, we have avoided making assumptions about the alternatives available. Instead, we have deduced the alternatives from data on the activities of members of our sample. The tax and transfer levels we attribute to AFDC are derived from a regression study of the benefits received by the dependent members of the sample, and the wage rates are derived from a regression of actual wages received on personal characteristics for a large number of wage-earners. This procedure guards against some sys-

tematic errors: We know that assistance is available on the terms we specify in our study because we observe many members of our sample receiving those benefits, and we know that work is available at the wage we specify because we observe many women at work at those wages, at a great variety of hours per week. Other systematic errors remain. In particular, we are unable to deal with differences in the probability of finding work at all or of being accepted for public assistance after applying. Comparisons between blacks and whites are especially sensitive to these differences. Our finding that whites are slightly more likely than blacks to receive assistance, everything else equal, may reflect discrimination on the part of welfare administrators as well as differences between black and white attitudes about welfare. In general, our results on the sensitivity of the probability of dependence to observed family characteristics should be interpreted as the reduced form arising from the interaction of the behavior of families, employers, and AFDC administrators. Through the preliminary regressions for earnings and AFDC benefits, we have removed much of the influence of family characteristics that operate indirectly through employment opportunities or benefits, and have assigned the influences to explicit variables--the wage and the parameters of the benefit schedule. Some indirect influence remains, however, and should be kept in mind in interpreting the results.

In addition to these systematic differences, there are purely random differences in economic opportunities not associated with any of the family characteristics we observe. The evidence suggests that there is a good deal of this dispersion. In the benefit equation of our ealier study, the residuals had standard errors of $17 to $53 per month. Dispersion in the wages paid to apparently identical women is also large--the wage equations used to impute wages had standard errors of more than 40 percent (the

regressions are in log form). The probabilities estimated in the present study combine the effects of the underlying diversity of families with the effects of the diversity in opportunities available to apparently identical families.

2. Functional form and statistical method

For reasons to be discussed shortly, we do not estimate the probabilities $p_0(x),\ldots,p_3(x)$ of our four levels of dependence for the population, but deal instead with the probabilities $g_0(x),\ldots,g_3(x)$ within our sample. Since the $g_i(x)$'s are probabilities, they should be non-negative and should sum to one. The logit functional form provides a convenient way to impose these properties. It is

$$g_i(x) = \frac{\exp(x\beta^{(i)})}{1 + \exp(x\beta^{(1)}) + \exp(x\beta^{(2)}) + \exp(x\beta^{(3)})}, \qquad (2.1)$$

$$i = 1,2,3;$$

$$g_0(x) = \frac{1}{1 + \exp(x\beta^{(1)}) + \exp(x\beta^{(2)}) + \exp(x\beta^{(3)})}. \qquad (2.2)$$

Here $\beta^{(1)}$, $\beta^{(2)}$, and $\beta^{(3)}$ are vectors of parameters associated with partial dependence, substantial dependence and total dependence, respectively. The probability of zero dependence, $g_0(x)$, is obtained as a residual; this is an arbitrary normalization and the same results would be obtained if any of the other three were treated as the residual. Provided that the vector of characteristics, x, used in the specification can include dummy variables and other nonlinear transformations of the original variables, the logit specification can approximate any multinomial probability $g_0(x),\ldots,g_3(x)$ to any desired precision. The use of the logit specification involves no restrictive assumption about the distribution of unobserved differences among individuals.[1]

---

[1] See footnote on p. 14A.

---

[1] The discussion of Daniel McFadden and others of the relation of the logit specification to the strict utility model of the theory of stochastic choice may have given rise to some confusion on this point. In the theory of stochastic choice, it is the characteristics of the choices that enter the logit function, while the parameters deal with the characteristics of the decision-maker. In our work, the x's are the characteristics of the decision makers, and the characteristics of the choices (different degrees of dependence) are expressed by the parameters. Mathematically, our specification is a special case of the other specification, but the interpretation is rather different. Our work requires no questionable assumption about the "independence of irrelevant alternatives".

We estimate the parameters $\beta^{(1)}$, $\beta^{(2)}$, and $\beta^{(3)}$ by the method of maximum likelihood, using a computer program written by Meir Kohn. McFadden has studied the statistical properties of the maximum likelihood estimator for the logit specification, and has shown that the probability of its existence approaches one as the number of observations becomes large, and that it is consistent and asymptotically normal. The inverse of the matrix of second derivatives of the likelihood function converges to the variance-covariance matrix of the limiting distribution of the estimate and serves as an indicator of the sampling dispersion of the estimates in small samples.

Adjustment for the hybrid sample

A special problem of estimation arises in this study because of the nature of the data sources. Data on welfare recipients were taken from a survey of three percent of all recipients, while date on non-recipients were taken from a survey of about 0.1 percent of the population. Consequently, it is essential to take explicit and rigorous account of the nature of the sample in our statistical method. The statistical method just described gives estimates of the probabilities $g_0(x)$, $g_1(x)$, $g_2(x)$, and $g_3(x)$ that should be interpreted as the probabilities of the various levels of dependence conditional on being in the sample. In a purely random sample, this conditioning would have no effect and the $g_i(x)$ and $p_i(x)$ would be the same. In our case, however, $g_0(x)$ understates the true probability of zero dependence, $p_0(x)$, because the sample is so heavily weighted toward dependent families. The observed probabilities of positive levels of dependence, $g_1(x)$, $g_2(x)$, and $g_3(x)$, similarly overstate the true probabilities.

To give a clear probabilistic treatment of this bias, we define two random variables, k and r, for each family:

k = 0, 1, 2, or 3 for the category of dependence

r = 0 if the family is not in our sample

= 1 if it is

Our assumptions about the method of sampling can be stated conveniently by specifying the joint distribution of k and r:

Prob [k = 0 and r = 1] = $s_0(x)\ p_0(x)$, the probability that a family will not be dependent and will be sampled;

Prob [k = i > 0, r = 1 = $s_1 p_i(x)$, the probability that a family will be dependent and will be sampled.

Here $s_0(x)$ is the probability that a family with characteristics x that is not on welfare will be included in the sample of non-recipients and s_1 is the probability that a family on welfare will be included in the second sample. In principle, s_1 is independent of family characteristics, and, in any case, we have no way to measure it, so we assume that s_1 is exactly 0.03. In the first sample, however, the sampling rate depends explicitly on family characteristics, especially race; it deliberately oversamples poor nonwhite areas. It reports the sampling probability for each family, so it is possible to deduce the form of the dependence of s_0 on x. The method used to estimate the function $s_0(x)$ is described in the Appendix.

The observed conditional probability of zero dependence is:

$$g_0(x) = \text{Prob}\ [k = 0 | r = 1]$$

$$= \frac{\text{Prob}[k = 0 \text{ and } r = 1]}{\text{Prob}[k = 0 \text{ and } r = 1] + \sum_{i=1}^{3} \text{Prob}[k = i \text{ and } r = 1]}$$

$$= \frac{s_0(x)p_0(x)}{s_0(x)p_0(x) + \Sigma\ s_1 p_i(x)}$$

$$= \frac{s_0(x)p_0(x)}{s_0(x)p_0(x) + s_1(1 - p_0(x))} \qquad (2.3)$$

Unless $p_0(x)$ is close to 1 (very few families with characteristics x are on welfare) or is close to 0 (very few are not), $g_0(x)$ is substantially less than $p_0(x)$. For example, if $p_0(x)$ is 0.90 and $s_1/s_0(x)$ is 30, $g_0(x)$ is 0.23.

For positive levels of dependence, a similar relation holds between the observed conditional probabilities of dependence:

$$g_i(x) = \frac{s_1 p_i(x)}{s_0(x)\ p_0(x) + s_1(1 - p_0(x))} \tag{2.4}$$

To recover the $p_i(x)$ from the estimated $g_i(x)$, we solve equation 2.3 to get

$$p_0(x) = \frac{s_1 g_0(x)}{s_1 g_0(x) + s_0(x)(1 - g_0(x))} \tag{2.5}$$

Then from equation 2.4, we have

$$p_i(x) = g_i(x)(1 - \frac{s_1 - s_0(x)}{s_1}\ p_0(x)) \tag{2.6}$$

In the discussion of our results, we will refer to $g_i(x)$ as "unadjusted" and $p_i(x)$ as "adjusted".

3. Data

Data for the study were obtained from two sources. For families receiving assistance, data were taken from the survey of three percent of all recipients carried out in the fall of 1967 by the Social and Rehabilitation Service (SRS) of the Department of Health, Education and Welfare. Data for other families were taken from the Survey of Economic Opportunity conducted by the Bureau of the Census in March 1967. Only families consisting of a mother and one or more children were considered. Families with fathers present were not considered, but some families had additional adults.

The following variables were calculated for each family:

Degree of dependence, z: For non-recipients, zero. For recipients, total benefits, including all special and supplementary benefits, for the month preceding the survey, divided by earned income plus benefits, for the month.

Wage, w: Imputed by the method and for the reasons described in Hall. The imputed wage is a function of age, education, sex, race, city, and health. It is put in real terms by dividing by a geographic price index. It enters the equations in a piecewise-linear fashion, with breakpoints at \$0.00, 1.50, 2.00, 3.00 and 10.00 per hour. Wage coefficients at other wage levels can be calculated by linear interpolation.

Unearned income, y: All income from sources other than assistance or earnings of mother.

Maximum benefits, $\lambda + (1 - \tau)\, y$: Imputed by evaluating the benefit equation developed in Barr and Hall for each family, with earnings of the mother set to zero. The benefit equation takes account of

a variety of differences among cities in the administration of AFDC.

Tax rate on earnings, θ: Taken as the appropriate regression coefficient for earnings of mothers in the benefit equation in Barr and Hall. The only source of variation in tax rates is across cities.

Non-resident: Dummy variable, 1 if the family had not moved to the city in the past year.

Race: Dummy variable, 0 if mother is non-white, 1 if white.

Age: Dummy variable, 0 if the mother is 35 or lower, 1 if she is more than 35.

Health: Dummy variable, 0 if the mother is well, 1 if she is not.

Education: Set of dummy variables for the years of school of the mother; first is 1 if less than eighth grade, zero otherwise; second is one if twelfth grade or more and zero otherwise.

Children: Set of dummy variables; the first is 1 if there are more than two children and 0 if not; the second is 1 if there are any pre-school children and 0 if not.

Adults other than mother: Set of dummy variables; the first is 1 if there are one or two other adults and 0 otherwise; the second is 1 if there are 3 or more other adults.

The combined sample includes 11,839 families in nine cities.

4. Results

Our first step is the estimation of the parameters, $\beta^{(i)}$, of the unadjusted probabilities, $g_i(x)$. With these parameters, we can calculate the probability that a family drawn at random from our sample with characteristics x, will not be dependent at all ($g_0(x)$), partially dependent ($g_1(x)$), substantially dependent ($g_2(x)$), and totally dependent ($g_3(x)$). Then by applying formulas 2.5 and 2.6 we can calculate the corresponding probabilities $p_0(x)$, $p_1(x)$, $p_2(x)$ and $p_3(x)$ for families drawn at random from the population of the United States. Since the second set of probabilities is the one of interest for almost any application of our results, most of this section is devoted to a discussion of them.

Table 1 presents the estimated coefficients and standard errors for the unadjusted probabilities. These should be interpreted in terms of the logit specification,

$$g_0(x) = \frac{1}{1 + \exp(x\beta^{(1)}) + \exp(x\beta^{(2)}) + \exp(x\beta^{(3)})} \qquad (4.1)$$

$$g_i(x) = \frac{\exp(x\beta^{(i)})}{1 + \exp(x\beta^{(1)}) + \exp(x\beta^{(2)}) + \exp(x\beta^{(3)})} \qquad (4.2)$$

$$i = 1,2,3.$$

If a particular characteristic has the same sign in all three of its appearances, its impact on the probability of dependence is unambiguous. For example, an increase in the tax rate on earnings clearly increases the probability that a family will not be on welfare at all. Similarly, within our sample a white family has a higher probability of receiving some degree of assistance than does a black family. In other cases, however, it is neces-

Table 1

Unadjusted Results

Characteristic	Degree of Dependence: Partial $\beta^{(1)}$	Substantial $\beta^{(2)}$	Total $\beta^{(3)}$
Wage, w (dollars per hour)			
0.00	-3.89	-2.05	-3.82
	(1.12)	(1.09)	(0.87)
1.50	3.50	2.08	4.37
	(0.67)	(0.70)	(0.61)
2.00	4.62	2.50	4.40
	(0.73)	(0.77)	(0.67)
3.00	3.15	1.05	1.90
	(0.91)	(1.00)	(0.82)
10.00	-0.99	-2.49	2.89
	(6.51)	(7.57)	(4.42)
Unearned income, y (hundreds of dollars per month)	-1.48	-1.45	-1.31
	(0.16)	(0.17)	(0.13)
Non-resident	-4.26	-0.48	-4.19
	(0.39)	(0.73)	(0.19)
Income without work, $\lambda + (1 - \tau)$ y (hundreds of dollars per month)	-0.50	-0.16	0.25
	(0.29)	(0.30)	(0.27)
Tax rate on earnings, θ	-3.01	-2.56	-1.80
	(0.87)	(0.92)	(0.72)
Race			
Black	0	0	0
White	0.43	0.50	0.70
	(0.19)	(0.21)	(0.17)
Age			
35 or less	0	0	0
More than 35	1.40	-0.66	-1.34
	(0.18)	(0.20)	(0.16)
Health			
Well	0	0	0
Sick	-1.02	0.01	0.86
	(0.29)	(0.25)	(0.19)
Education			
Less than 8th grade	1.08	0.89	1.40
	(0.21)	(0.22)	(0.18)
8th to 11th grade	0	0	0
12th grade or higher	-0.46	-0.39	-0.53
	(0.27)	(0.31)	(0.24)

Table 1 (Continued)

Characteristic	Degree of Dependence		
	Partial $\beta^{(1)}$	Substantial $\beta^{(2)}$	Total $\beta^{(3)}$
Children			
2 or fewer	0	0	0
More than 2	0.76	0.69	0.39
	(0.12)	(0.13)	(0.12)
At least one child of pre-school age	0.03	-0.24	0.63
	(0.18)	(0.19)	(0.15)
Other adults			
None	0	0	0
1 or 2	-0.50	-0.21	-0.71
	(0.16)	(0.17)	(0.15)
More than 2	0.00	0.08	0.08
	(0.10)	(0.11)	(0.09)

sary to evaluate formulas 4.1 and 4.2 to show how the probabilities vary with alternative values of the characteristics.

Adjusted results

In the rest of this section we will discuss the implications of our results in terms of the adjusted probabilities of the four degrees of dependence. We compute these from the coefficients of Table 1 for the unadjusted probabilities and from the coefficients of Table A2-1 for the sampling probabilities. In some cases, notably the effects of race and the wage rate, the adjustment is substantial. Our discussion starts from the probabilities of dependence for a hypothetical benchmark family with the following characteristics: the mother is black, healthy, has less than 12 years of education but more than 8, is capable of earning $1.50 per hour, has three children, none of preschool age, and no other adults in the family, and lives in a city that provides a lump-sum payment, λ, of $200 per month and taxes the mother's earnings at 40%. A very large fraction of our sample with these characteristics is dependent on public assistance; even after adjustment for our oversampling of this kind of family, the probabilities of dependence, especially of total dependence, is quite high. Only 9 percent of the population with the benchmark characteristics avoids dependence altogether, while 81 percent have no earnings and are totally dependent. The remaining 10 percent supplement their benefits through work.

Effects of wages and unearned income

Women with the benchmark characteristics have almost no alternative to public assistance because the market offers them so little for their work. The probabilities of dependence are strikingly lower for women whose services

are more highly valued, as shown in Table 2. At $2.00 per hour, the probability of being off welfare completely is only slightly higher, but the probability of combining earnings and benefits is almost twice as high. The probability of total dependence is 13 percentage points lower than for the benchmark case. At a wage of $3.00 per hour, almost half the families are off welfare and less than a third are totally dependent.

The probability of dependence is also sensitive to the amount of unearned income, y, as shown in the second part of Table 2. In these calculations, we are holding constant the income available from public assistance without working, $\lambda + (1 - \theta)\, y$. As y rises, income off welfare rises while income on welfare remains the same, so families shift off welfare altogether. Thus increasing y to $200 reduces the probabilities of both total and intermediate degrees of dependence. This effect is to be contrasted with the effect of rising wages, which stimulate a shift toward partial dependence as well as a shift to zero dependence.

Effects of race, education, age, health, family composition and length of residence

Table 3 presents the adjusted probabilities of dependence for variations in each of the other characteristics included in the model. In each section of the table, one of the characteristics varies while all of the others are held constant at their benchmark values. The first characteristic is race. After taking account of the other observed characteristics of families, especially wages, income, education, and number of children, almost no pure difference between blacks and whites remains. In fact, whites are slightly less likely than blacks to escape dependence completely, and are somewhat more likely than blacks to be fully dependent. The disproportionate number of blacks on welfare is not the result of differences in attitudes about

Table 2

Adjusted Probabilities of Dependence by Wage Rate and Amount of Unearned Income

	Degree of Dependence			
	None	Partial	Substantial	Total
Wage, w				
1.50	9%	7	3	81
2.00	10	17	5	68
3.00	44	21	5	30
Unearned income, y				
0	9	7	3	81
200	58	2	1	39

Table 3

Adjusted Probabilities of Degrees of Dependence by Various Characteristics

Characteristics	Degree			
	None	Partial	Substantial	Total
Race				
Black	9%	7	3	81
White	8	5	3	84
Education				
Less than 8 years	3	5	2	90
8 thru 11 years	9	7	3	81
12 years or more	13	7	4	76
Age				
Less than 35	9	7	3	81
35 or above	27	5	6	62
Health				
Good	9	7	3	81
Poor	4	1	2	93
Children				
1 or 2, none preschool	14	4	3	79
3 or more, none preschool	9	7	3	81
1 or 2, at least one preschool	8	3	1	88

Table 3 (Continued)

Characteristics	Degree			
	None	Partial	Substantial	Total
Other Adults				
None	9	7	3	81
1 or 2	17	7	5	71
3 or more	8	6	4	82
Time in present city				
Less than 1 year	88	1	0	11
1 year or more	9	7	3	81

welfare between blacks and whites, but a reflection of the adverse circumstances of blacks.

The second characteristic in Table 3 is education. Since education also enters the formula for calculating the imputed wage, which is held constant here, these are the pure effects of education apart from its influence on the financial attraction of work. With everything else held constant, including the wage, more highly educated women are more likely to be off welfare and less likely to be fully dependent. The probability of partial dependence is not strongly influenced by education. The total impact of education could be calculated from these pure effects combined with the indirect effects via the wage.

The results in Table 3 for the effect of age are somewhat surprising. Again, the wage variable takes account of the tendency for older women to earn more. The variables for the number and ages of children and the number of other adults in the family take account of the systematic differences in family composition that are associated with a mother's age. Still, older women are much less likely to depend on public assistance. It is an interesting question whether this is an age or a generation effect - will the current generation of young mothers have the lower probabilities of dependence of today's older mothers when they are older?

Poor health has precisely the expected effect in our results. All but 7 percent of women reporting some disability are fully dependent, against 19 percent of women who are identical in every respect but health.

Three alternative combinations of the two variables measuring the number and age of children are reported in Table 3. Mothers with 3 or more older children are less likely to be off welfare, more likely to supplement benefits with earnings, and about as likely to be fully dependent, compared to mothers with one or two older children. The presence of younger children

causes a substantial increase in the probability of full dependence. This illustrates the importance of schools as custodial institutions, implicitly supplementing family income and making dependence less likely.

The presence of extra adults in the household (including children of working age) should presumably reduce the probability of dependence. Thia is true in our results for one or two extra adults, but not for three or more. We are unable to explain the latter finding. The standard errors in Table 1 suggest that it is not a statistical fluke.

Finally, length of residence in the city has a dramatic effect on the probability of dependence. This is not so much the result of individual choice as a reflection of the administrative provision of AFDC in 1967, when most states imposed a one-year residency requirement.

Effects of taxes and transfers

The parameters of the benefit formula have an important impact on the probability of dependence. More generous formulas, that is, those with higher lump-sum components, λ, and lower tax rates, θ, are more attractive than less generous formulas. This is shown in Table 4, where we present probabilities of dependence for the benchmark family, first holding θ constant at 0.4 and letting λ vary, and then holding λ constant at $200 per month and letting θ vary. Everything else held constant, raising λ from $150 to $250 raises the probability of total dependence from 77 percent to 84 percent. Most of this comes from families that were partially dependent at the lower value of λ - the probability of zero dependence only falls from 10 to 8 percent.

The effect of changes in the tax rate on earnings appears mainly in the probabilities of zero and partial dependence. Increasing the tax rate from 0.2 to 0.6 raises the fraction of families who are off welfare alto-

Table 4

Adjusted Probabilities of Alternative Degrees of Dependence by Values of Parameters of Benefit Formula

Parameter	Degree of Dependence			
	None	Partial	Substantial	Total
Lump-sum Component, λ				
150	10%	9	4	77
200	9	7	3	81
250	8	5	3	84
Tax rate on earnings, θ				
0.2	6	9	4	81
0.4	9	7	3	81
0.6	12	5	3	80

gether from 6 to 12 percent and reduces the fraction who are partially dependent from 9 percent to 5.

The implications of the effects of the parameters of the benefit formula are shown in greater detail in Table 5. Here we have solved for the values of monthly hours of work, H, and monthly benefits paid, b, by substituting the benefit formula into the definition of z:

$$z = \frac{b}{b + wH} \tag{4.3}$$

$$= \frac{\lambda - \theta wH}{\lambda + (1 - \theta)\, wH}\,, \tag{4.4}$$

provided $z > 0$. Thus

$$H = \frac{\lambda(1 - z)}{\theta w + (1 - \theta)\, zw} \tag{4.5}$$

if $z > 0$ and is undefined otherwise. Our study says nothing about the hours of work of those not on welfare. Next,

$$b = \lambda - \theta wH \tag{4.6}$$

$$= \frac{z}{\theta + (1 - \theta)\, z} \tag{4.7}$$

Formulas 4.5 and 4.7 show that starting from our measure of dependence z, and our knowledge of the relation of benefits to earnings, we can solve for the numerator and denominator of z and thus obtain H and b. The results of this calculation for the benchmark family are shown for the four ranges of z in Tables 5 and 6. We have taken $z = 0.4$ for partial dependence and $z = 0.8$ for substantial dependence. The numbers in this part of the table are derived purely from the benefit formula and the definition of z and are not related to the probabilities estimated in this study. The aggregate impact of changes in

Table 5

Effects of Parameters of Assistance on Hours of Work for the Benchmark Family

Parameter	Degree			Expectation		
	None	Partial	Sub-total	Total	Whole Population	Recipients
Lump-sum Component, λ						
$150	150	94	23	0	24	11
200	150	125	30	0	23	10
250	150	156	38	0	21	9
Tax rate on earnings, θ						
0.3	150	138	31	0	23	13
0.4	150	125	30	0	23	10
0.5	150	114	30	0	24	9
0.6	150	105	29	0	25	7

Table 6

Effects of Parameters of Assistance on Net Benefits for the Benchmark Family

Parameter	Monthly Benefits by Degree of Dependence				Expectation	
	None	Partial	Sub-stantial	Total	Whole Population	Recipients
Lump-sum component, λ						
$150	0	94	136	150	130	144
200	0	125	182	200	176	194
250	0	156	227	250	224	244
Tax rate on earnings, θ						
0.3	0	138	186	200	179	194
0.4	0	125	182	200	176	194
0.5	0	114	178	200	173	193
0.6	0	105	174	200	170	193

λ and θ can be appraised from the expected value of hours of work, H, and net benefits, b, over the entire population. For hours, this requires an estimate of monthly hours of work for non-recipient mothers with the benchmark characteristics. We use 150 hours, somewhat less than full time. The expected values are

$$E(H) = \sum_{i=0}^{3} p_i(x)\, H_i \tag{4.8}$$

and

$$E(b) = \sum_{i=0}^{3} p_i(x)\, b_i \tag{4.9}$$

where $p_i(t)$ are the probabilities from Table 4 and H_i and b_i are from Tables 5 and 6. We also calculate the conditional expectations of H and b for the population of recipients:

$$E(H|z > 0) = \sum_{i=0}^{3} \frac{p_i(x)}{1 - p_0(x)}\, H_i \tag{4.10}$$

and

$$E(b|z > 0) = \sum_{i=0}^{3} \frac{p_i(x)}{1 - p_0(x)}\, b_i \tag{4.11}$$

In Table 5, expected hours of work have the anticipated negative relation to the lump-sum component of the benefit formula, both for the whole population and for recipients. An increase of $50 per month in benefits depresses average hours of work by about 10 percent in both cases. On the other hand, increases in the tax rate on earnings <u>increases</u> the aggregate volume of work (as measured by the expected value of hours of work in the whole population),

even though it decreases the hours of work of the average welfare recipient. This runs counter to a great deal of recent thought about the relation between income supplements and the supply of labor. Taken literally, it suggests that a reform of AFDC in the direction of lower implicit taxes on earnings would reduce the total supply of labor. Such a reform would bring enough additional families under welfare, each of which would reduce its supply of labor, to compensate more than fully for the increased hours of work of those already on welfare.

Table 6 presents comparable results for net benefits paid. In the benchmark case (λ = \$200, θ = 0.4), the average family receives \$176 per month in benefits, while the average dependent family receives \$194 per month. An increase in λ from \$200 to \$250 increases benefits per family by \$48 and benefits per dependent family by \$50. The second figure represents the exact cancellation of two opposing influences: Raising λ makes families who were previously on welfare even more dependent, and so, would make the increase per family even more than \$50, but it also brings new families onto welfare at lower levels of dependence who lower the average. Increases in the tax rate, θ, reduce the amount of benefits paid to the average family but leave benefits paid to the average dependent family almost unchanged. The latter reflects the fact that increases in θ reduce the proportion of families who are not fully dependent and so removes from the average families who are below the average.

Summary by city

As a final summary of our results, we present in Table 7 the probabilities of alternative degrees of dependence for the eight cities of our previous study for which we have estimates of the parameters of the benefit formulas. Chicago,

Table 7

Adjusted Probabilities of Dependence by City

City	Tax on earnings, θ	Lump-sum λ	Degree of Dependence			
			None	Partial	Sub-stantial	Total
Baltimore	0.50	186	11%	7	3	79
Chicago	0.39	207	9	7	3	81
Detroit	0.55	215	11	5	3	81
Houston	0.21	101	8	16	5	71
Los Angeles	0.35	207	7	8	4	81
New York	0.34	253	8	5	3	84
Pittsburgh	0.18	192	7	9	4	80
San Francisco	0.39	215	9	6	3	82
Wash. D.C.	0.72	162	15	6	3	76

Source for θ and λ: Barr and Hall, Table 1.

Los Angeles, and San Francisco have intermediate values of both parameters and are closest to the benchmark case illustrated earlier in Figure 1. Baltimore and Detroit have higher tax rates and about the same lump-sum components, so they have somewhat higher probabilities of zero dependence. Washington, D.C. has by far the highest θ, 0.72, and a fairly low λ, \$162. As a result, it has much the highest probability of zero dependence, close to the lowest probabilities of partial and substantial dependence, and almost the lowest probability of total dependence. Houston competes with Washington, D.C. as the least attractive city in the opposite way. Because it taxes earnings at a low rate but provides little income for non-workers, it has by far the highest probability of substantial dependence. Pittsburgh has a tax rate even lower than Houston's but pays almost twice as much to non-workers. It has the lowest proportion off welfare altogether. Finally, New York has much the highest lump-sum component and thus almost the highest proportion of fully dependent families. Its tax rate is sufficiently high to keep 8 percent of the benchmark families off welfare.

References

P. Albin and B. Stein, "The Constrained Demand for Public Welfare Payments", Journal of Human Resources, Vol. III, pp. 300-311, Summer 1968.

N.A. Barr, Public Assistance and Family Behaviour in the Urban United States, Ph.D. dissertation, Dept. of Economics, University of California, Berkeley, 1971.

C.T. Brehm and T.R. Saving, "The Demand for General Assistance Payments", American Economic Review, Vol. 54, pp. 1002-1018, December 1964.

R.E. Hall, "Wages, Income, and Hours of Work in the U.S. Labor Force" in G. Cain and H. Watts, Labor Supply and Income Maintenance: Econometric Studies, Rand McNally, 1973, pp. 102-162.

R.E. Hall and N.A. Barr, "The Taxation of Earnings Under Public Assistance", Working Paper No. 131, Dept. of Economics, MIT, revised January 1974.

M.G. Kohn, The Cross-Section Processor, Dept. of Economics, MIT, June 1972 (processed).

Daniel McFadden, "Conditional Logit Analysis of Qualitative Choice Behavior" in P. Zarembka (ed.) Frontiers of Econometrics, Academic Press, 1974, pp. 113 -119.

J. Tobin, "Estimation of Relationships for Limited Dependent Variables", Econometrica, Vol. 26, pp. 24-36, 1958.

Appendix. Estimating the sampling probability for the SEO

The SEO reports the weight, w_i, to be applied to a family when forming aggregates. The weight is the inverse of the sampling probability. Our model of the sampling process is the following: Each family has probability $q(x,u)$ of being sampled, where x are reported characteristics and u are unreported characteristics. The weight for the ith family is

$$w_i = \frac{1}{q(x_i,u_i)} \tag{A.1}$$

We are interested in

$$s_0(x) = \int q(x,u)\ f(u)\ du\ , \tag{A.2}$$

the probability that a family chosen at random from among the population of families with characteristics x will be sampled. From the definition of w_i and $s_0(x)$, we have

$$\frac{1}{w_i} = s_0(x_i) + \varepsilon_i\ , \tag{A.3}$$

where the disturbance, ε_i, associated with our lack of knowledge of u_i obeys the basic hypothesis of a regression model: $E(\varepsilon_i|x_i) = 0$. We assume as a rough approximation that

$$\frac{1}{w_i} = x_i\alpha + \varepsilon_i \tag{A.4}$$

To estimate α, then, we simply regress $1/w_i$ on the reported characteristics, x_i. Fitted values from this regression are used in section 4 to adjust the estimated probabilities.

Table A-1 gives the estimates of α obtained from the SEO.

Table A2-1

Coefficients for SEO Sampling Probabilities

Characteristic	Coefficients and standard errors
Wage	
$0.00	.00680
	(.00072)
$1.50	.00252
	(.00037)
$2.00	.00174
	(.00038)
$3.00	.00224
	(.00052)
$10.00	-.00088
	(.00236)
Unearned income	-.00004
	(.00007)
Non-resident	-.00020
	(.00012)
Income without working	-.00003
	(.00014)
Tax rate on earnings	.00067
	(.00059)
Race	
Black	0
White	-.00111
	(.00014)
Age	
Less than 35	0
35 or higher	-.00008
	(.00013)
Health	
Well	0
Sick	-.00002
	(.00015)
Education	
Below 8th grade	-.00012
	(.00016)
8th through 11th	0
12th or higher	.00027
	(.00017)

Table A2-1 (continued)

Characteristic	Coefficients and standard errors
Children	
1 or 2	0
3 or more	.00014
	(.0007)
Preschool age	.00008
	(.00012)
Other adults	
None	0
1 or 2	-.00014
	(.00011)
3 or more	.00009
	(.00012)

8830 024

3113 135

[redacted]

[redacted]

NOV 2 1979

Date Due

Lib-26-67

MIT LIBRARIES
3 9080 003 672 109